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A Review on Electro Cardio Graph a New Approach

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Abstract

Abstract

An electrocardiogram (ECG) records the heart's electrical activity during a cardiac cycle. A lightweight system for analyzing ECG signal strength, aimed for real-time use and automatic classification, will be developed. This system will utilize ECG sensors, Arduino microcontrollers, Android phones, Bluetooth connectivity, and cloud servers, with a focus on ensuring secure data transfer. Lightweight Access Control (LAC) and Lightweight Secure IoT (LS-IoT) will be employed for this purpose. The paper also explores various types of ECGs and details the different waveforms typically observed. It provides interpretations of common ECG readings. The proposed IoT-based ECG monitoring architecture aims to enhance the reliability, accuracy, and efficiency of unsupervised diagnostic systems, potentially revolutionizing heart problem diagnosis and monitoring in clinical settings.

Keywords: *Electro Cardio Graph, normal ECG, Internet of Things (IoT), monitoring system, Light weight Access Control (LAC)*

INTRODUCTION

The article provides a comprehensive analysis of the electrocardiogram (ECG), tracing its origins from Augustus D. Waller's pioneering work in 1887 to modern advancements like smartphone-based ECG recording. It delves into the contributions of key figures such as Willem Einthoven, who coined the term "electrocardiogram" and developed crucial algorithms for enhancing ECG interpretation.

A significant breakthrough highlighted in the piece is the 2018 innovation of using smartphones for 12-lead ECGs. This method diverges from traditional practices by employing arm electrodes as reference points instead of the Wilson central terminal, greatly enhancing the accessibility and convenience of ECGs. This advancement has the potential to reshape cardiac monitoring both in clinical settings and beyond.

The article also recounts Einthoven's groundbreaking work at St. Mary's Hospital in London, where he conducted the first electrocardiogram in 1887 using a mercury capillary electrometer and a toy train. His subsequent discoveries, including the correction formula for the Lippmann capillary electrometer, revolutionized ECG interpretation. The corrected waveforms he identified, such as PQRS and T, have since become fundamental in ECG analysis.

Overall, the article underscores the historical significance and ongoing evolution of ECG technology, pointing towards a future where cardiac monitoring is more accessible and efficient thanks to innovative methods like smartphone-based ECG recording.

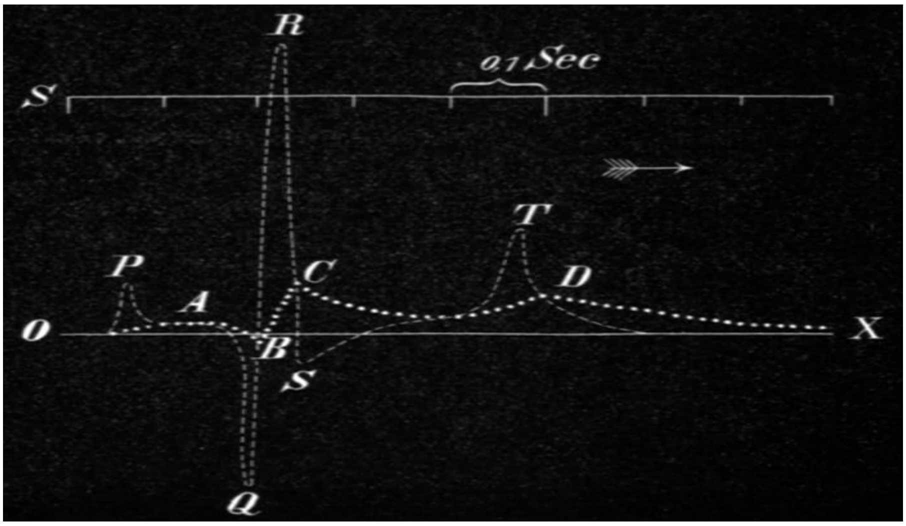

Fig.1. P,Q,R,S,T, waves in 1895

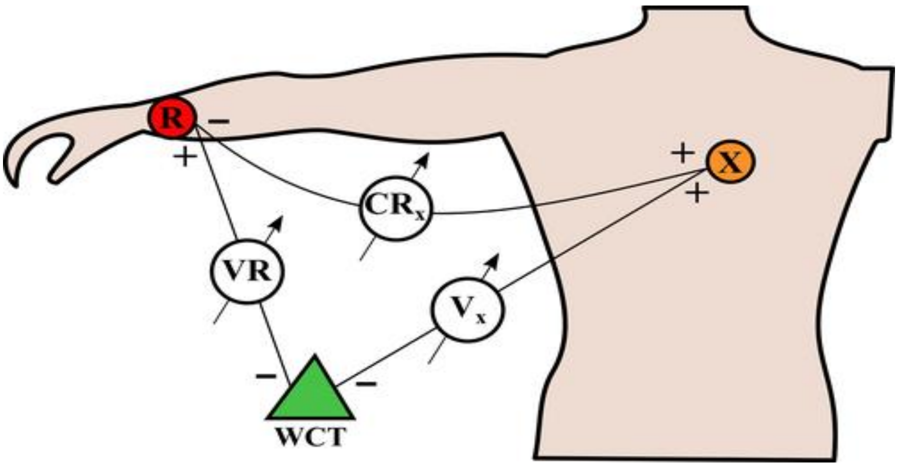

Fig.2.Electrode arrangements of recording leads

The arrangement of electrodes for Vx and CRx recording leads. The electrode on the right arm is denoted by R, while one of the six electrodes on the chest is represented by x (1–6). Wilson Central Terminal is known by its acronym, WCT.
Kirchoff's second law states that the potentials represented by the voltmeter symbols (Vx, CRx, and VR) are

CRx=Vx-VR=Vx-(2/3).

The same criteria apply to all chest leads (V1–V6, CR1–CR6).
Should the left arm be used as a reference, then VL and aVL will be substituted for VR and aVR in the computation.
Using the right or left arm electrode as the reference, the objective of this study was to compare the amplitudes of the chest-lead ST-J to those of the standard 12-lead ECG. Furthermore, we aimed to evaluate the sensitivity and specificity of the smartphone 12-lead ECG, which is based on these reference electrodes, for the identification of STEMI, in comparison to the outcomes obtained with the conventional 12-lead ECG.

The time at which the ST-J amplitudes in each of the 12 leads were measured was known as the J-point, which is also known as the end of the QRS and the beginning of the ST segment.

$$\text{R as reference: } CR_x = Vx - \frac{2*aVR}{3}$$

$$\text{L as reference: } CLx = Vx - \frac{2*aVL}{3}$$

The V leads, CR and CL leads, and ST-J elevations of ≥0.1 mV in all but V2 and V3 (≥0.15 mV for women, ≥0.2 mV men ≥40 years, and 0.25 mV men <40 years) were subjected to the STEMI criteria [4-5].
One disadvantage of the 12-lead ECG on smartphones with CR or CL leads is that its sensitivity for identifying STEMIs is slightly lower.
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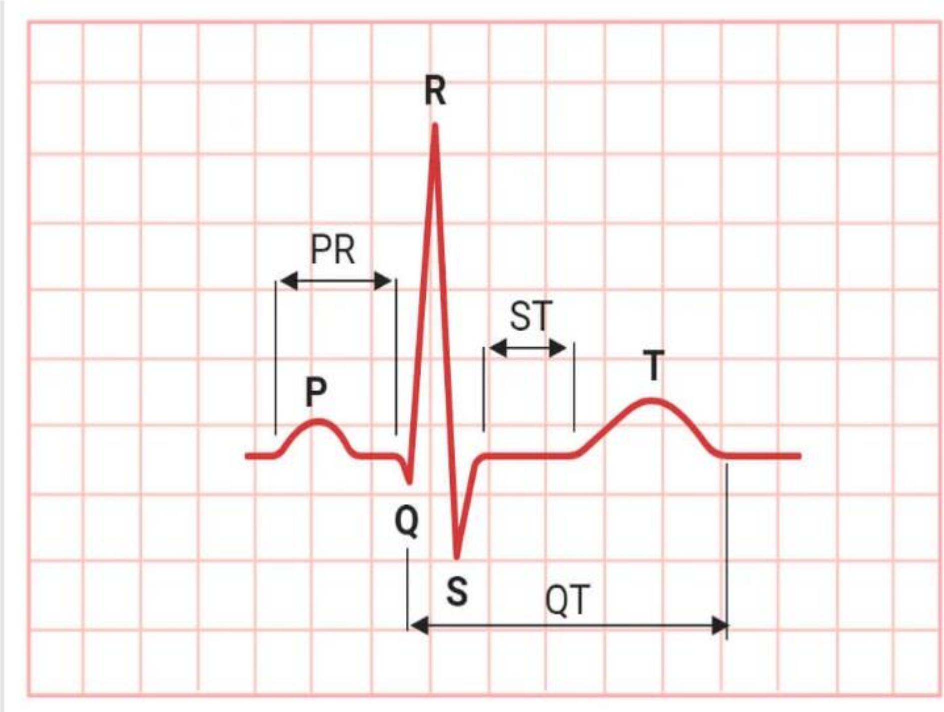

Fig.3 Graph of ECG

An electrocardiogram, or EKG, is a medical test that tracks the electrical activity and rhythm of the heart across several cardiac cycles. This information is typically recorded on grid paper, also known as an ECG strip or tracing. Electrocardiography, the process of establishing an ECG, is the non-invasive monitoring of cardiac impulses with specific electrodes placed on body regions. The primary purpose of an ECG is to identify and diagnose any structural heart abnormalities or cardiovascular issues. Cardiologists routinely recommend ECG testing to patients to gain additional insight into the electrical functioning of their hearts (see figure 3).
During an ECG examination, electrodes attached to the body collect electric potentials, also known as biopotentials. The biopotentials are sent via lead cables to a central signal processor located within the ECG apparatus. This gadget generates ECG waves at preset intervals and segments by processing, filtering, and amplifying this data. The resulting signals are printed onto grid paper and displayed on a monitor to make an exhaustive ECG report.
All things considered, an ECG machine is a vital tool for monitoring and assessing cardiac activity, providing vital information for the identification and management of numerous heart-related conditions.

Principle of Electrocardiogram

The electrocardiogram (ECG) records the electrical activity of the heart, which is regulated by the cardiac action potential and cardiac conduction system. The sinoatrial (SA) node in the right atrium functions as the body's natural pacemaker, initiating the cardiac action potential. This electrical impulse then passes via the cardiac conduction channel, contracting the myocardial cells and changing the membrane voltage (potential) across their membranes.
The cardiac action potential, as it passes through the heart, starts a sequence of events known as the cardiac cycle. The phases of the heart chambers' depolarization (contraction) and repolarization (relaxation) during this cycle are depicted in the electrical signals captured by the ECG. By displaying the variations in electrical activity that takes place in the heart at

each stage of the cardiac cycle, the ECG provides crucial information on the rhythm and function of the heart.

Types of ECGs

There are three main types of ECG, that are:

1. **Resting ECG**
   It is the typical ECG form that is frequently employed in hospital settings for diagnostic purposes. It is carried out while lying motionless in bed.
2. **Exercise ECG**
   It is the ECG taken while engaging in physical activity, most commonly walking on a treadmill or riding a stationary bike. Known by a different name, the stress test monitors the electrical activity of the heart in response to physical stress.
3. **Ambulatory ECG**
   It is a kind of ECG that shows a heart's continuous electrical activity for at least 24 hours. In this kind, the patient wears a tiny, portable ECG device called a Holter monitor around their waist and is permitted to resume regular work for at least a day. The ECG is examined from the Holter machine after a predetermined amount of time.

ECG Waves in a normal Electro Cardio Graph

Three separate waves can be seen in a typical ECG: the P-wave, the QRS-complex, and the T-wave.

1. **P-wave**
   Atrial depolarization can be seen in the ECG as the first minor upward wave. It stands for the electrical activity that initiates atrial systole, or the impulse that the SA node generates and transmits immediately prior to the onset of atrial systole.
2. **QRS-complex**
   The second, larger, vertical, triangular-shaped wave that is substantially steeper and represents fast ventricular depolarization is called the QRS complex. The QRS complex is made up of three distinct waves: the S wave denotes the sharp descending deflection in the bigger upright triangular wave of an ECG, the R wave the sharp ascending deflection, and the Q wave the initial downward deflection. The ventricular depolarization or ventricular systole phases of a cardiac cycle correspond with the QRS complex.
3. **T-wave**
   It is the last upward deflection in the shape of a dome that indicates ventricular repolarization. The U-wave, a low amplitude, almost perceptible slight upward deflection, appears in some ECGs immediately following the T-wave. This wave is thought to be caused by the repolarization of the interventricular septum.

Intervals in Normal ECG

The interval between the onsets of two waves in an ECG is measured and analyzed. These intervals show how long it takes for impulses to travel through the cardiac conduction system, resulting in a synchronized cycle of the heart wall's depolarization and repolarization. These periods of time are referred to as "intervals," and there are two primary types of intervals: the QT interval and the PR interval.

1. **PR Interval**
   The time interval between the start of the P-wave and the start of the QRS-complex on an ECG represents it. The PR interval is the amount of time the cardiac impulse

needs to travel from the SA node to the ventricles via the AV bundle, atria, and ventricles. Usually, it takes between 120 and 200 milliseconds.

2. **QT Interval**
   In an ECG, it is shown as the interval between the beginning of the QRS complex and the conclusion of the T wave. It stands for time that passes between successive ventricular depolarization and repolarization. Typically, it lasts less than 440 milliseconds [6].

Segments in a Normal Electrocardiogram

In an ECG, a "segment" is a flat, horizontal line that occurs between two subsequent waves, or from the end of one wave to the beginning of another. An ECG is composed of two primary segments: the PR segment and the ST segment.

1. **PR Segment**
   The PR segment is the flat line that appears between the end of the P-wave and the start of the QRS complex. It is a representation of the interval of time between the ventricular and atrial systoles. It takes a little bit more time than 440 milliseconds.
2. **ST Segment**
   The electrically neutral region between the end of ventricular depolarization and the start of ventricular repolarization is shown by the flat line between the QRS complex and T wave. Typically, it lasts for 80 milliseconds.

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Interpretation of ECG

Only professionals with the necessary training can analyze and interpret an ECG. The P wave, QRS complex, T wave, PR interval, QT interval, PR segment, and ST segment are the primary areas of interest when interpreting an ECG. The length of the segments and intervals, the elevation and depression of each wave, and the wave duration are all examined. Furthermore, an ECG's axis, rhythm, and heart rate are examined. An ECG report is interpreted using the combined outcome of all these different components. [7-8].
A normal ECG will show the following results:

1. **Heart Rate**: Normal heart rate of 60 to 100 beats per minute
2. **Heart Rhythm**: Heart rhythm will be consistent and even
3. **PR Interval**: 0.12 to 0.20 seconds
4. **QRS Duration**: 0.06 to 0.10 seconds
5. **QT Interval**: 0.40 seconds
6. **ST Segment**: 0.08 seconds

IoT Assisted ECG monitoring

A lightweight ECG monitoring system and other "things" that will aid in understanding the environment can be developed thanks to the Internet of Things (IoT) framework, which enables the design of tiny devices with sensing, processing, and communication capabilities.
The framework for IoT-assisted ECG monitoring is depicted in Figure 4. The primary benefits of an IoT-based system are lower treatment costs and higher care quality.

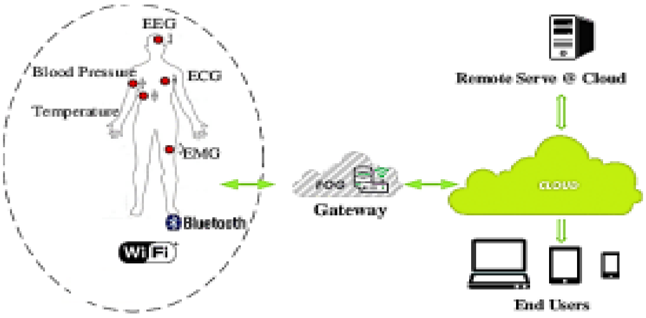

Fig.4.Structure of IoT based ECG monitoring system [10]

This makes use of networked biosensors to gather biomedical signals and transmit them to healthcare providers and the internet. [9]
To present a novel analysis of the intensity of IoT signals in the cardiovascular system. To put into practice a lightweight signal quality assessment approach to decrease bandwidth traffic and extend the battery life of wearable IoT devices.

MATHEMATICAL MODELLING

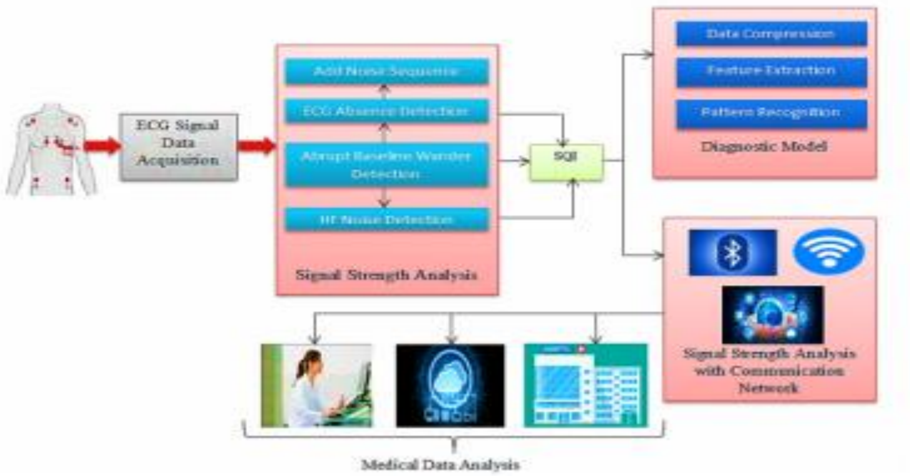

Fig. 5. Signal Strength Analysis framework based on IoT plat form

The main IoT platform components for signal strength analysis (SSA) are depicted in the figure 5. It is composed of three modules: (1) an automated module for signal quality evaluation, (2) an ECG analysis and transmitter module for signal quality assessment, and (3) an ECG module for signal sensing. This study evaluates the viability of the proposed SSA-IoT system under rest, patient, and physical activity situations. It focuses on the design and implementation of an automated ECG signal quality assessment procedure in real-time.
The flatline, or complete lack of an ECG signal, abrupt extraction, and high-frequency noise identification and extraction from the baseline are methods used to measure the intensity of

the ECG signal. The discrete filter, turning points, and decision-making guidelines based on the Fourier transform (DFT) are applied to the ECG-SSA.

Base line removal and Detection of abrupt change

Determining the local wave properties of the ECG beats becomes more challenging when the baseline wanders in sudden variations.
Less than 0.8 Hz is the baseline wandering frequency (up to 1 Hz when pressured).
To identifying fundamental faults, this makes use of the discrete filter method based on Fourier Transformation (DFT).

Let [p] p = 0, 1, 2, . . . q be an ECG signal of discrete-time.

The a [p] has been calculated as baseline wander detection.

$$A[h] = \sum_{p=0}^{p-1} a[p] e^{\frac{-ip\pi h}{p}} \qquad (1)$$

A[h]denotes the h^{th} DFT Coefficient. DFT coefficients of less than 1 Hz have been taken from the baseline.

$$h = \frac{FP.}{Fx} . y[p] = a[p] - \hat{a}\,[p] \qquad (2)$$

When the baseline wandering signal is y [p] and aˆ[p] is the baseline wandering removed signal calculated as

$$\hat{a}[p] = \frac{1}{p} \sum_{p=0}^{p-1} \hat{A}\,(h) e^{\frac{ip\pi h}{p}} \qquad (3)$$

The symbol Aˆ represents a vector containing the DFT threshold coefficient, which may be obtained as Aˆ (h) = [0,...... 0, A [h+1],... A [P–h – 1]]. An ECG signal generated from the baseline wander signal is shown in Figure 6. The baselines wander displays significant amplitude variation over a brief time span, according to the results. In order to differentiate between the abrupt baseline drift and baseline wanders that are beginning to change, this further analyzes the resulting signal.

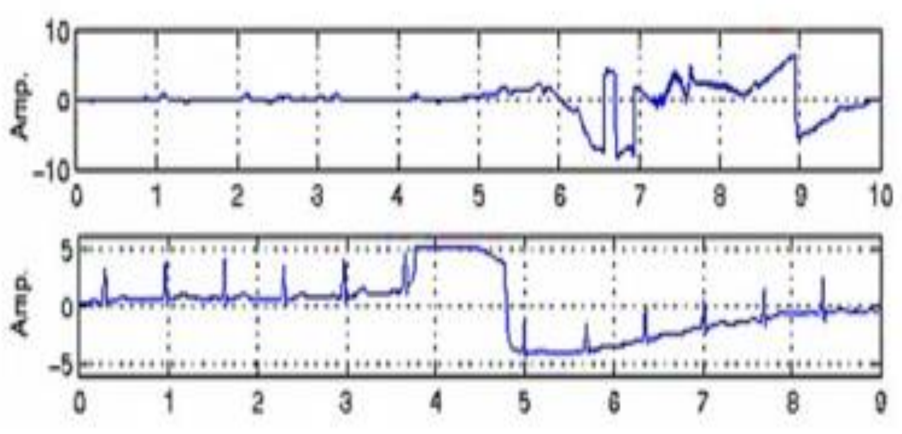

Fig.6. Abrupt baseline wandering detection

$$Xc = \max \{|y[p]|\}. \qquad (4)$$

where Xc is the dynamic value of amplitude. Baseline or abrupt baseline drift is noticed when Xc hits a predetermined threshold. It is possible to remove a fundamental component of an

ECG signal without affecting the other components. However, it is challenging to remove an abrupt baseline drift without affecting the other components of the ECG signal, which further analyzes the abrupt baseline drift signal.
The baseline wandering removed signal is computed as follows where the baseline wandering signal is y [p] and aˆ[p].

$$\hat{y_h}(p) = y\left(\frac{Ch}{2} + p\right) \quad p = 1, 2 \ldots . T \qquad (5)$$

Next, the predefined threshold is compared with the approximate zj of the accurate baseline drift situation.

$$SQI_{ABD} = \begin{cases} 1, & \max\{|z|\} > \beta \\ 0, & \text{otherwise} \end{cases} \qquad .(6)$$

For the abrupt baseline drift event (ABD), when the SQIABD is associated with the Signal Quality Index (SQI). Here, 0.2 mV is used as the β to identify sudden baseline drifts that can alter the ST segment and other low-frequency ECG signal components. When there is sudden baseline wandering, the ECG signal is deemed unsuitable. Because it can be retrieved from a sample without significantly altering the PQRST complex, the ECG signal is a good signal.

QUALITY GRADING OF THE ECG SIGNAL (QGS) This section measures the ECG signal based on decisions made regarding abrupt baseline wandering, the lack of an ECG signal, and high-frequency sounds. The ECG signal is classified into three groups, such as good, medium, and bad, based on ratings for HF noise. Having abrupt and flat simple wanderings can be a contributing factor to clinical symptoms that are loud. Based on the evaluation's findings, it was found that the ECG signal with a few high-frequency disturbances may compute certain morphological traits and RR intervals. Therefore, the ECG signal with noise is rated as terrible and medium. Ultimately, the signal's quality is assessed as

$$\begin{cases} Good, SQI = 0 \\ Medium, SQI = 0.5 \\ Bad, SQI => 0.5 \end{cases}$$

ABSENCE DETECTION OF ECG SIGNAL

Because the skin and the electronic saturation components are not linked to the electrodes, the sensor displays an absence of ECG signal information in the signal obtained. In actuality, the graph displays the existence of the physiological and external noise, the only moving baseline, and the flat line of zero amplitude (ZFL). Existing methods have been developed for ZFL event detection. It offers a fresh method for locating the noise events listed above in this study.
This is how the flat line detection is explained:

Add very small equally distributed random noise to the
a [p] k [p] = ˆa [p] + xr (p) .(8)
The signal is subjected to random noise for a predetermined number of turning points. The A scale has an amplitude of 0.01 mV. The distorted signal k [p] has multiple turning points if there is no ECG. Determine the number of turning points (tp) for a noisy signal k [p] by using a criterion. Determine the number of turning points (tp) with the threshold for a noisy signal k [p].

$$SQI_{FT} = \begin{cases} 1, & tp > 0.66M \\ o, & othewise \end{cases}$$

DETECTION OF HF NOISE

The ECG signal is produced by high-frequency noises (HF), which include noise, delay, motion artifacts, power line interference, and muscle artifacts. The HF sounds have the potential to disrupt the ECG signal's local waves (P, T, U, and the low amplitude QRS). As a result, determining the frequency, length, pause distance, time, polarity, and forms of the local waves is challenging and requires confidence. It is particularly difficult to eliminate HF sounds and muscle noise without changing the local signal waves. Thus, this work offers a fundamental method for identifying HF noise using the turning points and threshold rule: When normalizing the ECG signal, use the maximum amplitude.
Segment the normalized signal aˆ [p], into blocks of the block size (S) of 2 s which are not overlapped.

aˆh (p) = ˆa (Sh + p) p = 1, 2, ...S ……………………….(9) where h = 0, 1 . . . Q1 − 1 and

Q1 = Q S * A µH amplitude threshold of 0.05 mV for calculation of turning points on the basis of an appropriate HF noise level, that does not distort small amplitude waves on the local ECG signal.

$$SQI_{HF} = \begin{cases} 1, & G_1 \| G_2 \\ o, & othewise \end{cases}$$

QUALITY GRADING OF THE ECG SIGNAL (QGS)

This section measures the ECG signal based on decisions made regarding abrupt baseline wandering, the lack of an ECG signal, and high-frequency sounds. The ECG signal is classified into three groups, such as good, medium, and bad, based on ratings for HF noise. Having abrupt and flat simple wanderings can be a contributing factor to clinical symptoms that are loud. Based on the evaluation's findings, it was found that the ECG signal with a few high-frequency disturbances may compute certain morphological traits and RR intervals. Therefore, the ECG signal with noise is rated as terrible and medium. Ultimately, the signal's quality is assessed as

$$QGS = \begin{cases} Good, & SQI = 0 \\ Medium, & SQI = 0.5 \\ Bad, & SQI => 0.5 \end{cases}$$

Then SQI is measured as $SQI = SQI_{ABD} + SQI_{FT} + SQI_{HF}$ …………………(10)

The moderate and low quality of noise levels are shown in moderate and terrible indications; however, the good quality of the ECG signal shows that noise levels are suitable, and the morphological traits do not distort. This presupposes that ECG-specific signal processing systems may use the medium class of ECG signals.

MATHEMATICAL MODEL FOR SECURE ECG DATA TRANSMISSION LIGHTWEIGHT ACCESS CONTROL (LAC)

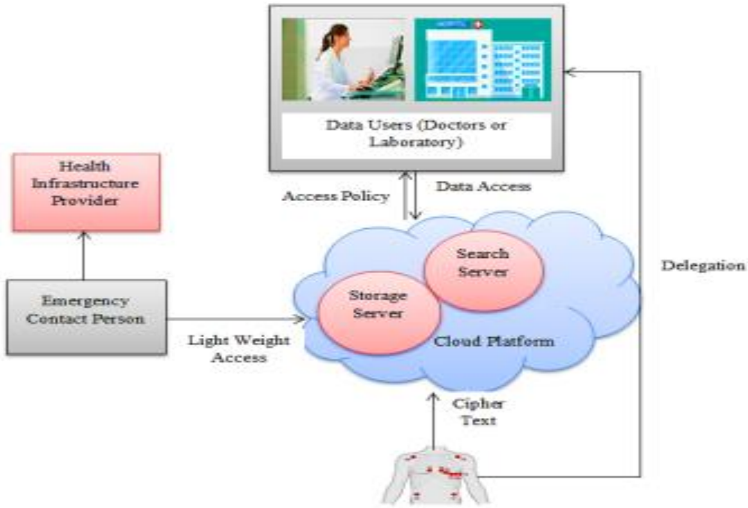

Fig.7. Lightweight access control for secure ECG data transmission.

Lightweight Access Control (LAC) for transmissions Figure 7 illustrates the architecture of the LAC, which consists of the primary data generation core, a cloud platform (PT), data owners, patients, data consumers, and an emergency contact person.

LIGHTWEIGHT SECURE IoT (LS-IoT) The LSHS consists of five components: the key generating center (KGC), patients, edge servers (ES). It includes the cloud server and doctors, as shown in Figure 8. In the lightweight, secure health care data transmission system, each part plays the following role:

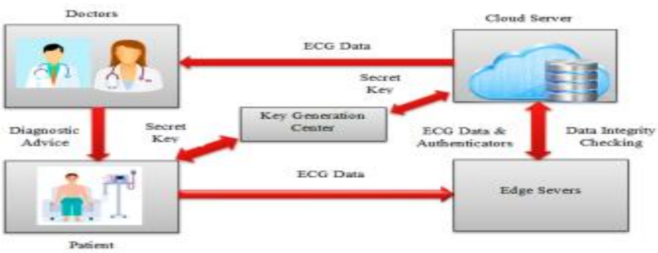

Fig.8. LS-IoT based secure data transmission.

- The KGC creates secret keys to verify their identification to patients and edge servers, as well as initializes the system.
- Every patient is connected to specific sensors by the suggested lightweight, secure health storage system. These sensors record ECG data from patients. For patient care, this kind of ECG data is kept on a cloud server.
- To reduce its own pressure, the sensors immediately encrypt ECG data before sending it to the next-end edge server for processing.
- The purpose of the patient edge server is to measure the level of patient health information authentication and transfer the data and authentication to the cloud server.
- To verify that the ECG data they save on their cloud server is legitimate, patients can send public data to any edge server.
- The patient's encrypted ECG data is stored by the CS. When a physician requests access to a patient's ECG data, CS verifies the physician's identification and provides the physician with the decrypted ECG data.

- Medical professionals review patient ECG information kept on a cloud server and offer patients the necessary guidance.

COMPUTATION COST

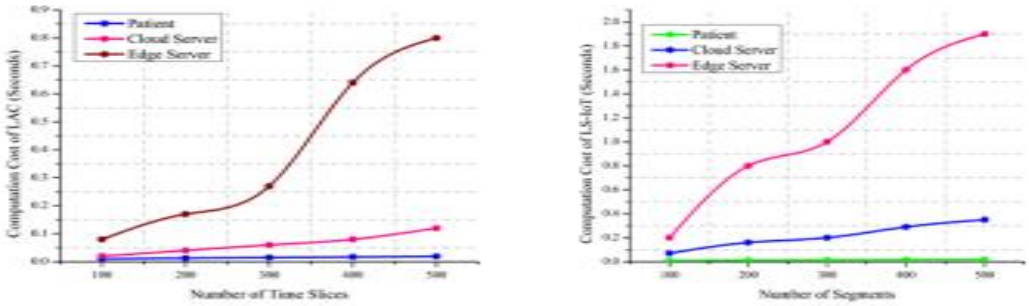

Fig 9. the computation cost of (a)LAC and (b)IoT

The computation cost of LAC and IoT is displayed in Figure 9. Based on the arguments and data above, the IoT approach has a stronger ECG signal.

CONCLUSIONS

This overview covers the evolution of the Electrocardiogram method. explains the operation and fundamentals of typical ECG signals after that. Along with the introduction of a novel IoT-assisted signal analysis framework for cardiac health surveillance applications, an ECG-SSA approach is proposed for the automated assessment of the quality of ECG signals obtained in relation to patient and physical activity. Better security for ECG data transfer is provided by Lightweight Access Control (LAC) and Lightweight Secure IoT (LS-IoT). According to this study, by lowering the false alarm levels for significant ECG noise recordings, the use of ECG Signal Strength Analysis (SSA) with an Internet of Things device that supports cardiac health control has a great deal of potential to improve the resource effectiveness, security, and reliability of non-controlled signal analyzers and diagnostic systems. Future improvements to the ECG health monitoring will be made possible by sophisticated machine learning algorithms.

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